Needs for Physical Models and Related Methods for Development of Automated Road Vehicles

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Automated Driving

(a)

(b)

Figure 1.: Driverless concepts: Volvo Vera (a) and 360c Concept (b) Volvo Trucks and Volvo Car Group, respectively)

Figure 2.: Volvo external steering [22]

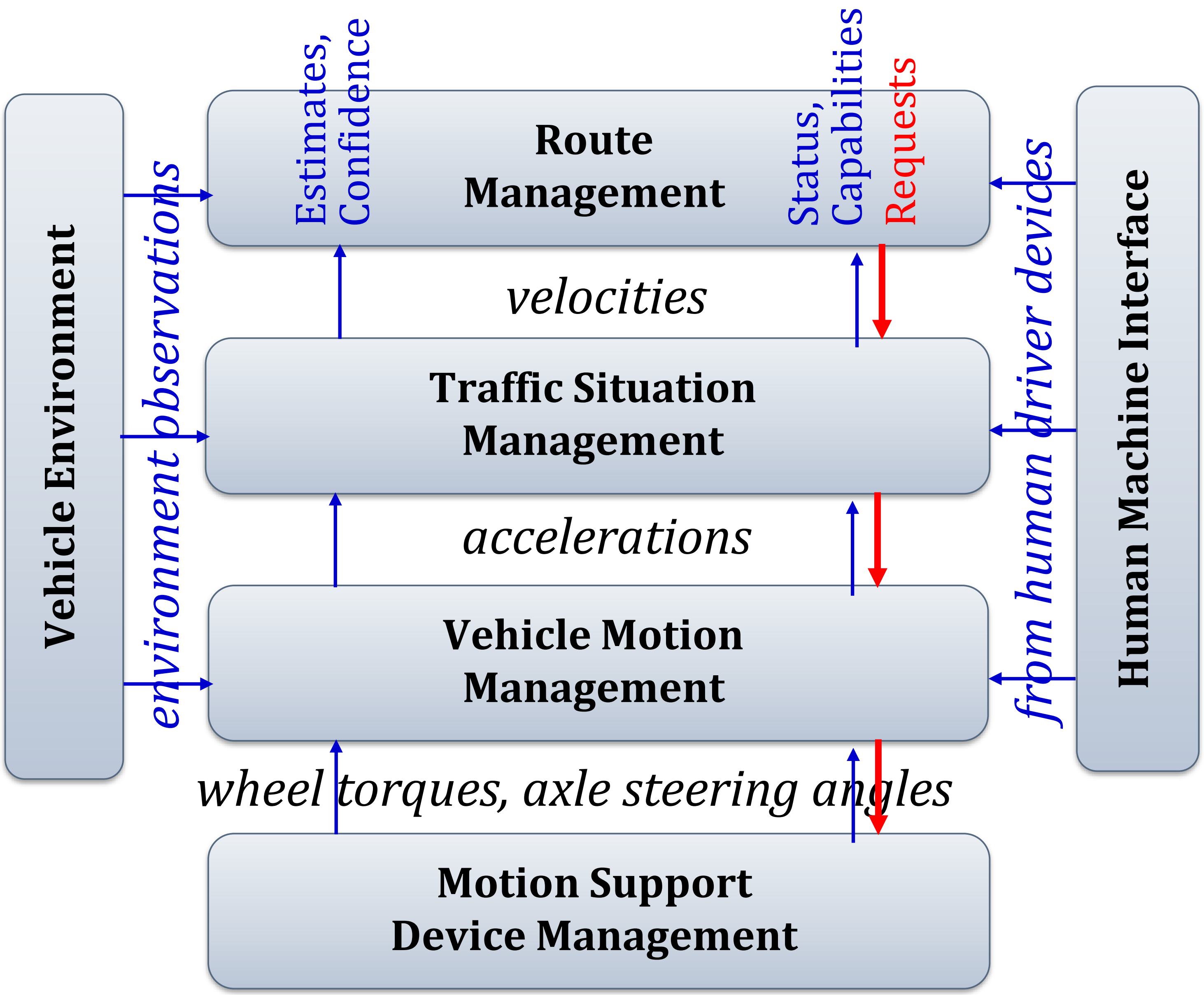
Reference: [Matthijs Klomp, et al, 2019]

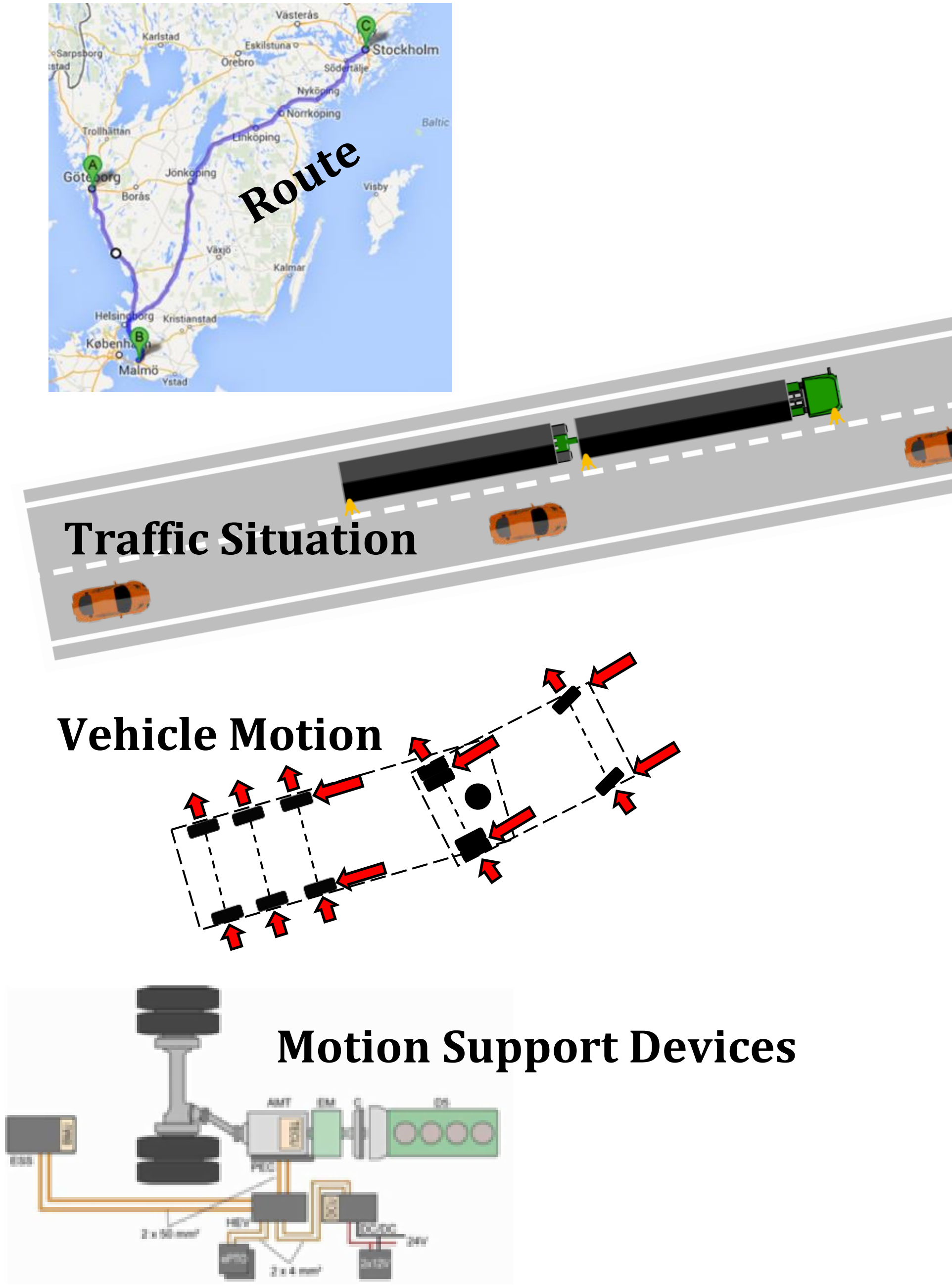
SAE J3016

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	**No Automation**	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	**Driver Assistance**	the *driving mode*-specific execution by a driver [illegible]sistance system of either steering or accelerati[illegible]ion using information about the drivin[illegible] with the expectation that the *hum*[illegible]rform all remaining aspects of the *dynamic d*[illegible]*ing task* ACC or LKA	Human driver and system	Human driver	Human driver	Some driving modes
2	**Partial Automation**	the *driving mode*-specific execution by one or more driver assistance systems of both steering and accelera[illegible] deceleration using information about th[illegible] environment and with the exp[illegible]*uman driver* perform all remaining a[illegible] *the dynamic driving task* ACC and LKA	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	**Conditional Automation**	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	**High Automation**	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* [illegible]t respond appropr[illegible]ely to a *request to in*[illegible] Fig 1 a)	System	System	**System**	Some driving modes
5	**Full Automation**	the full-time p[illegible]rmance by an *au*[illegible]*riving system* of all aspects of the *dynamic driving* [illegible] *task* under all roadway and environmental conditions that can be managed by a *human driver* Fig 1 b)	System	System	System	**All driving modes**

Reference: [SAE, 2014]

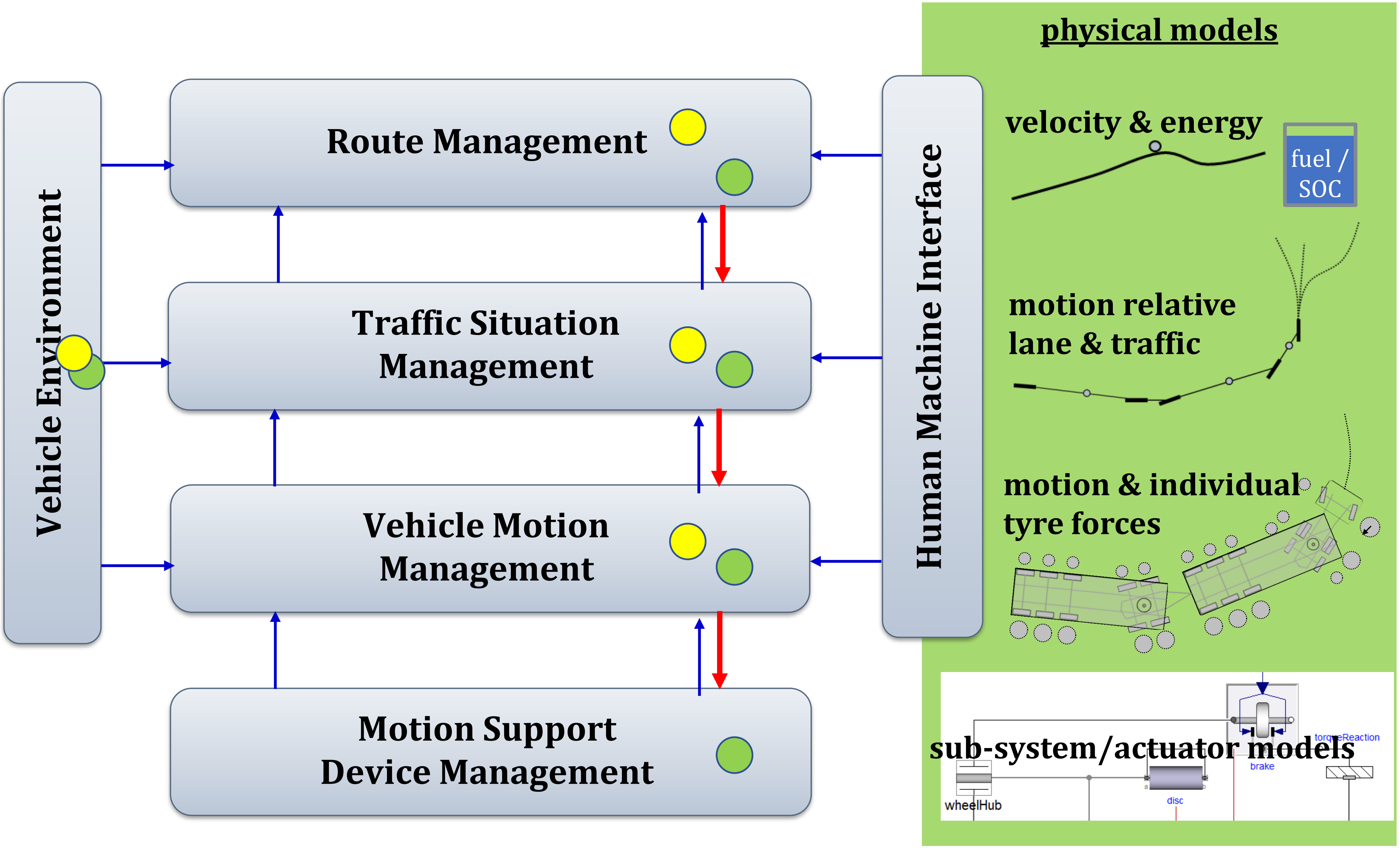
“*Function Architecture*” for vehicle motion & energy





Reference: [Nilsson, 2017]

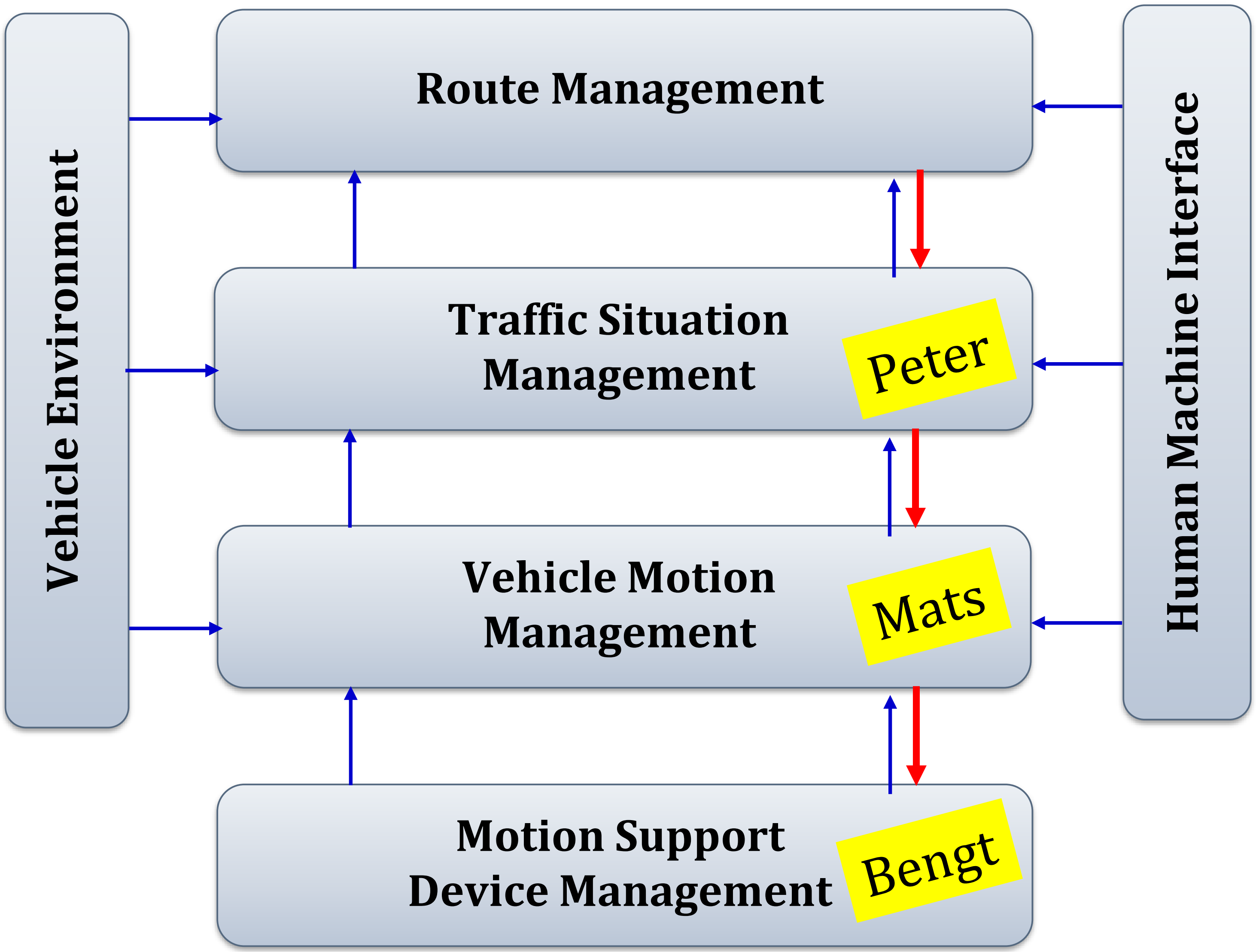
Models for vehicle motion and energy control design



data-driven models

- macro traffic
- drivers
- micro traffic
- estimators

Next speakers



Traffic Situation Management, Dynamically Feasible Trajectories, Peter Nilsson, Volvo Trucks

Examples of challenges for TSM

Behaviour planning (Tactical decision)

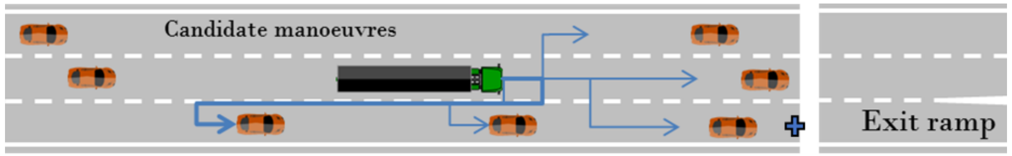
Predictions of surrounding traffic and VRUs

Sensor imperfections and occlusions

Situation assessment

Consistent and predictable behaviour

Computational efficient methods



Functional safety

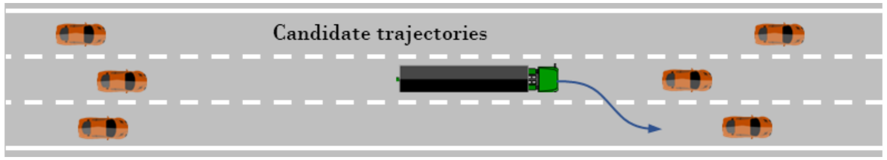
Motion Planning (Trajectory planning)

Predictions of surrounding traffic and VRUs

Collision free trajectories

Dynamically feasible trajectories

Comfortable and predictable trajectories



Vehicle Longitudinal and Lateral Control

Robust control

Thrust and comfort

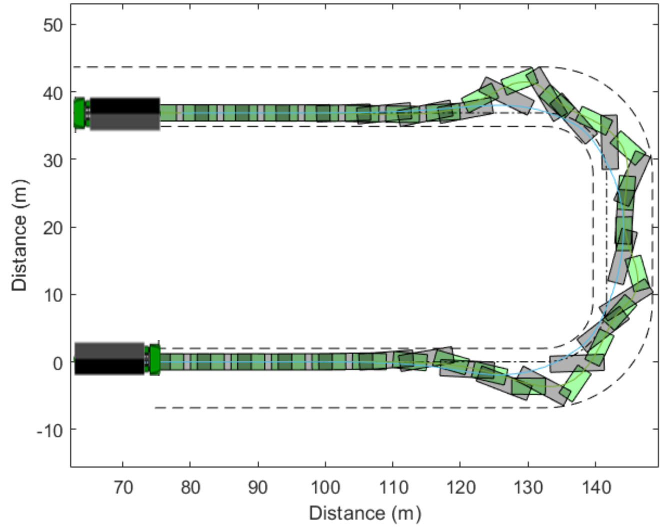
Transitions between driving modes

Trajectory planning

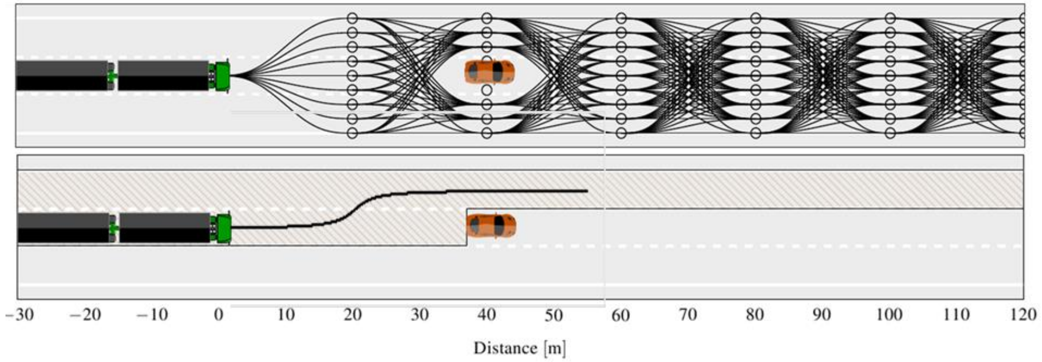
"Trajectory planning is a generalization of path planning, involved with planning the state evolution in time while satisfying given constraints on the states and actuation"

Commonly used methods:

- Numerical optimization (e.g. MPC)
- Graph search (e.g. A*)
- Neural network (e.g. Nvidia PilotNet)
- ...



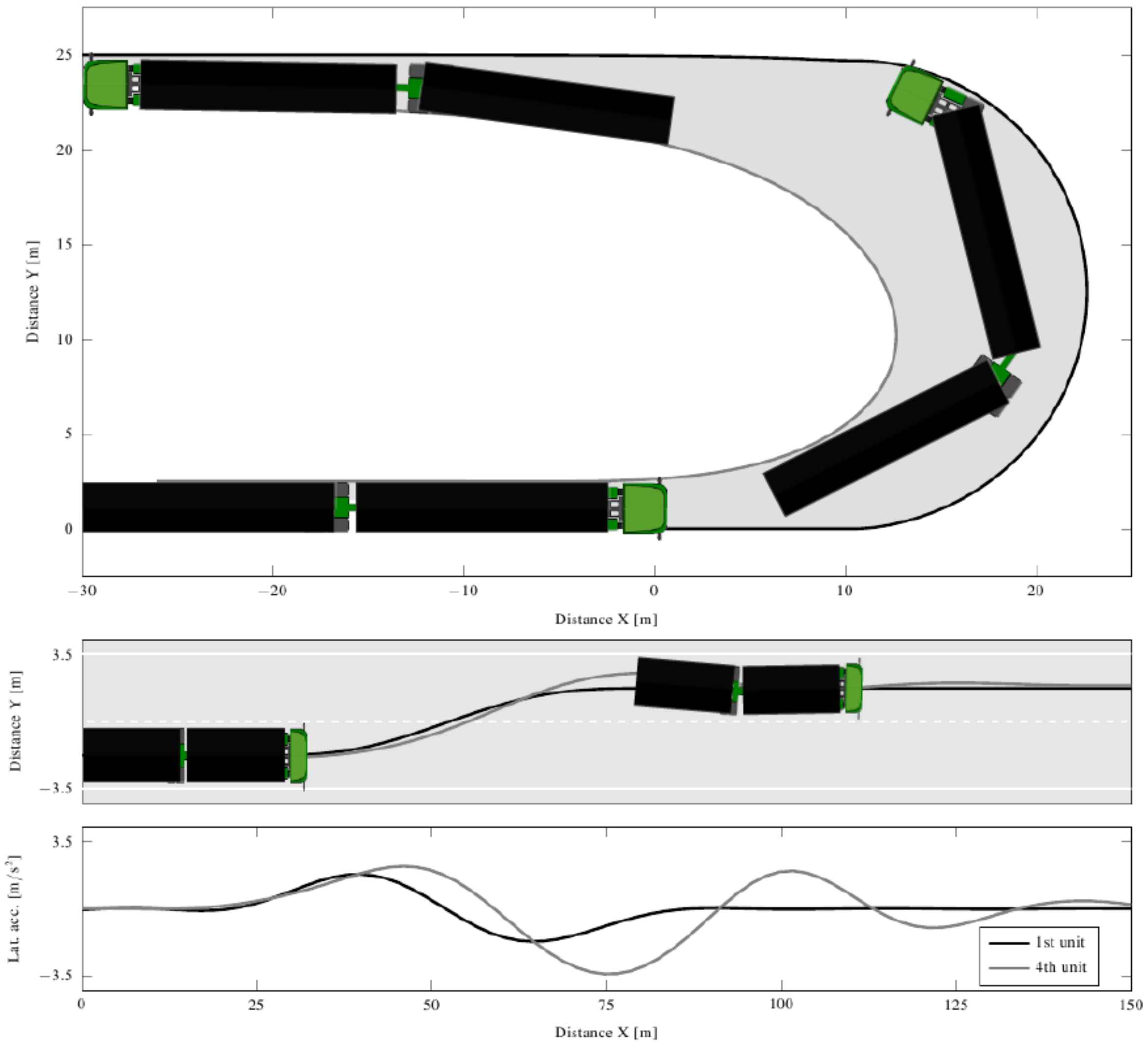
Trajectory planning example:
left curve, tractor semi-trailer



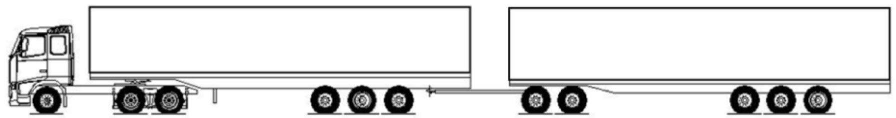
Heavy duty combination vehicles

Example of motion constraints:

- Position of first unit
- Position of trailer units (off-tracking)
- Roll-over threshold (rearward amplification)
- …

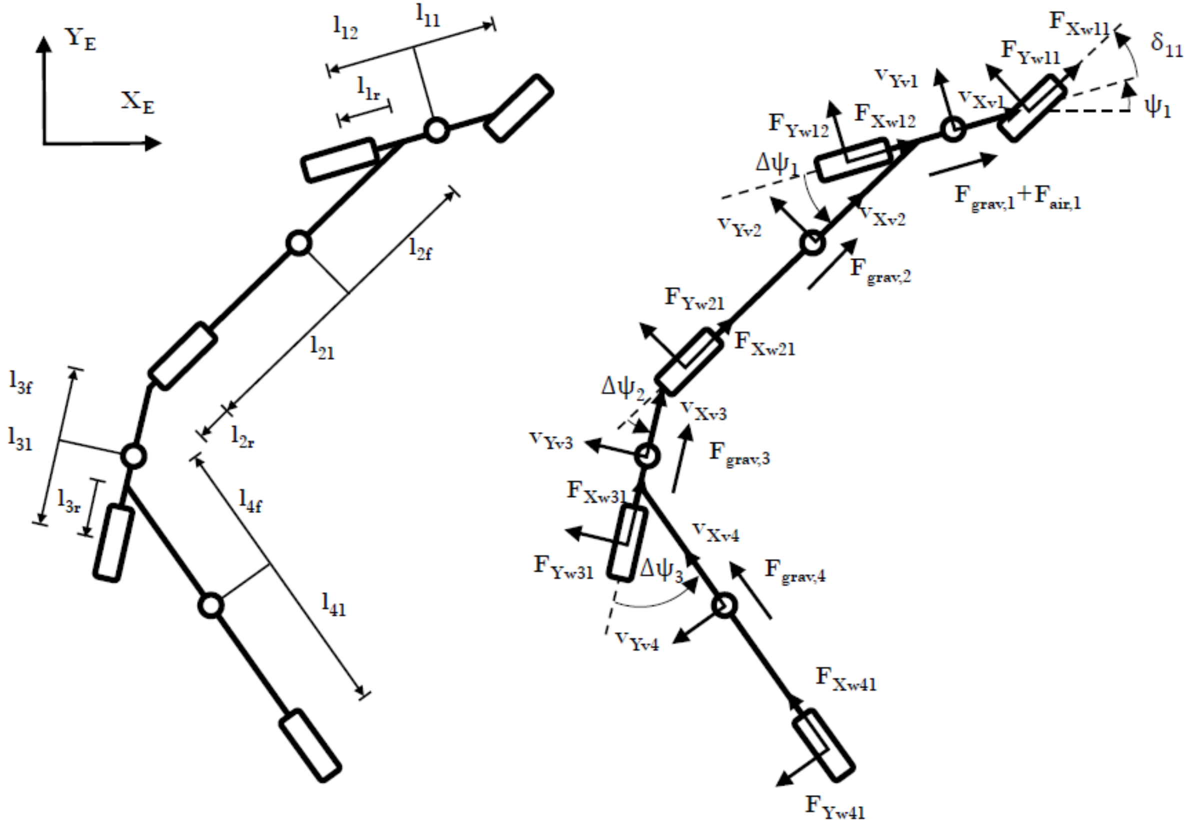


Trajectory planning modelling



Example of modelling:

- One-track models : $\dot{x} = f(x, u, w)$
- Possible states for A-double
    - 1st unit (tractor) : $v_x, v_y, \dot{\psi}_1$
    - 2nd unit (trailer) :$\Delta\psi_1, \Delta\dot{\psi}_1$
    - 3rd unit (dolly) :$\Delta\psi_2, \Delta\dot{\psi}_2$
    - 4th unit (trailer) :$\Delta\psi_3, \Delta\dot{\psi}_3$



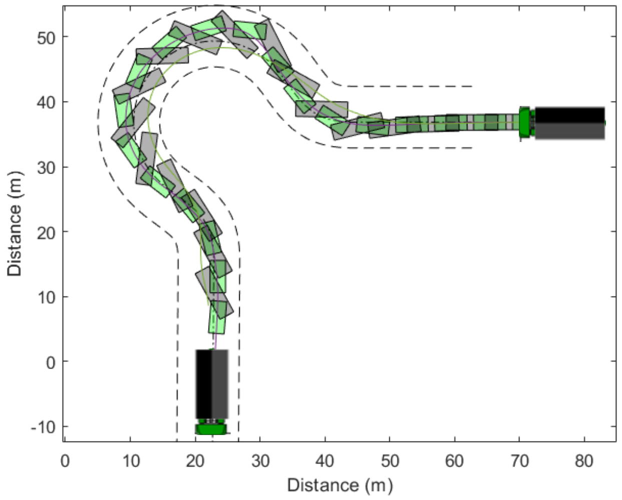
Vehicle variants and trajectory planning challenges

Vehicle variant combinatorics:

- Powertrain : ≈ 10^2 variants
- Chassis : ≈ 10^3 variants
- Vehicle load ≈ 7 - 120t (incl. different heights to CoG)
- Vehicle units : 1-4

Challenge:

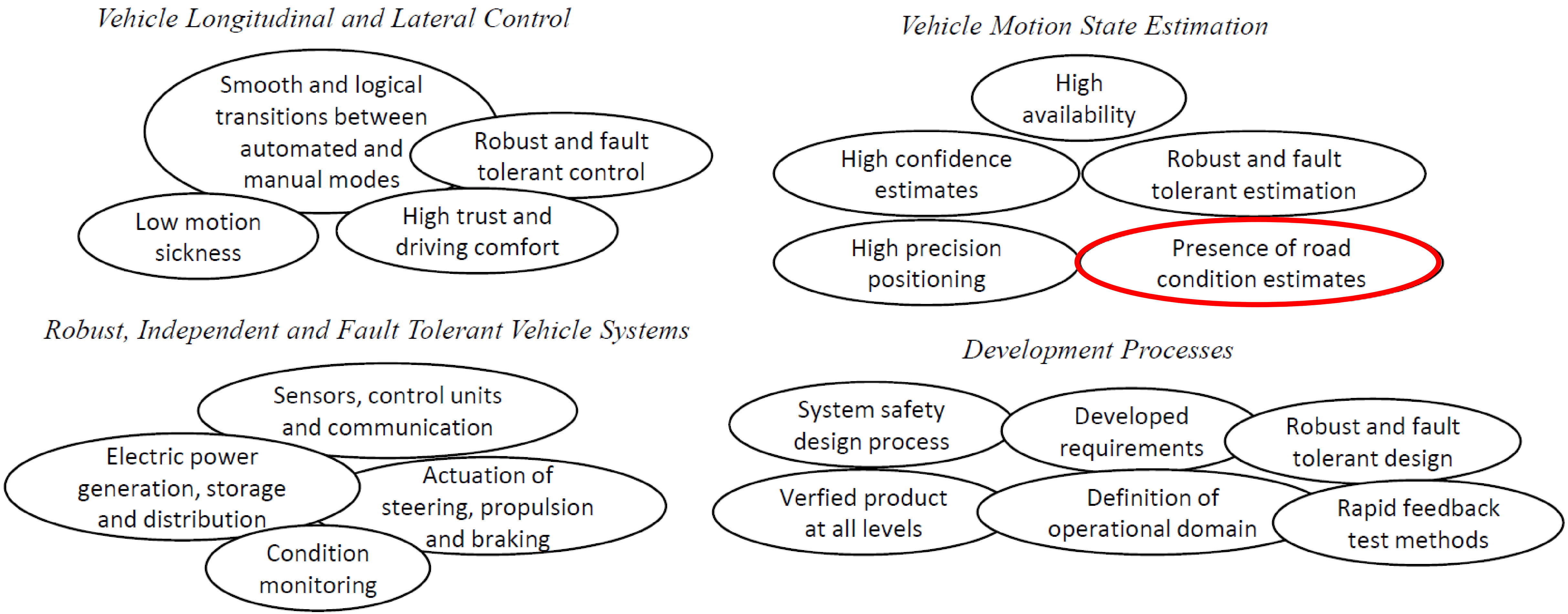
Trajectory planning methodology needs to scalable and robust with respect to variant combinatorics



Trajectory planning example:
Roundabout, tractor semi-trailer

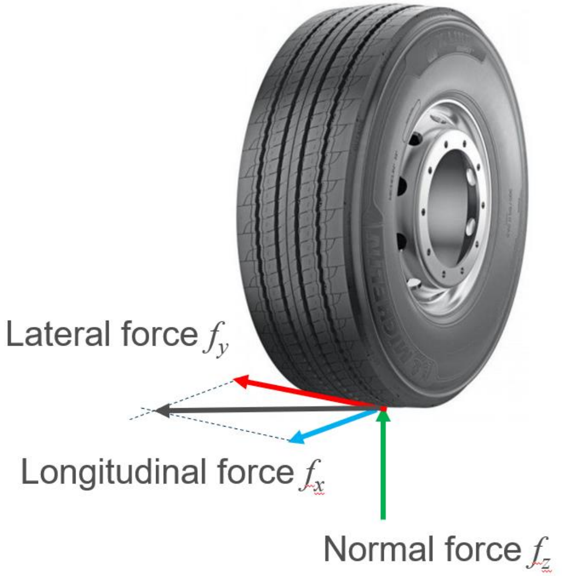
Vehicle Motion Management,
Road friction estimation,
Mats Jonasson

Challenges for VMM



Reference: [Matthijs Klomp, et al, 2019]

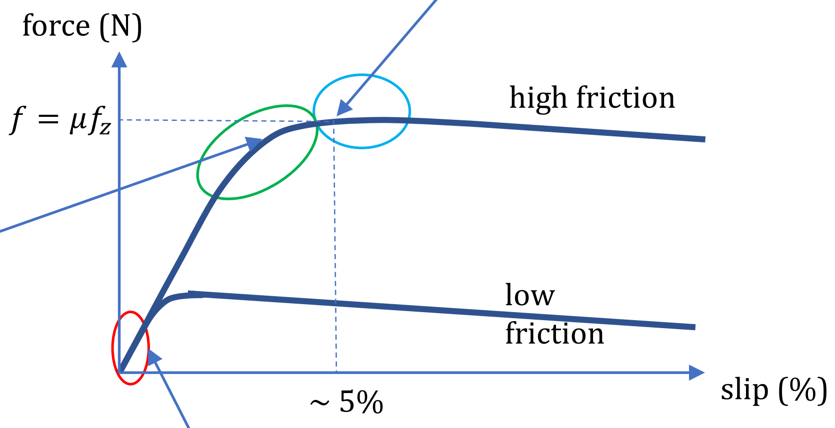
Road condition – road friction



More than 10% of all accidents occur because of slippery conditions*

In the US: yearly approx 500 000 accidents of which 1800 are deadly*

ABS activation, friction can be found $\mu \approx \frac{f}{f_z}$



To estimate friction the tyre must at least be excited to the nonlinear region at "the bend"

Definitions:

Low friction	$0 < \mu \leq 0.4$
Mid friction	$0.4 < \mu \leq 0.7$
High friction	$0.7 < \mu$

Most driving take place here, not possible to distinguish between low or high friction

* Reference: [IVSS Road Friction Estimation Part II]
* Reference: [US Department of Transportation – Federal Highway Administration
** Reference: [Wallman. Tema vintermodell – olycksrisker vid olika vinterväglag]

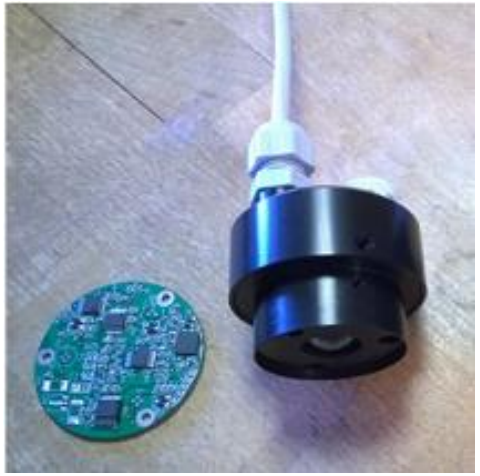
Confusion matrix of road friction

Assumed friction \ True friction	Low (snow)	High (dry asphalt)
Low (snow)	Vehicle speed can be adapted to friction	• False slippery warnings • AD Vehicle will drive unacceptably slow (not transport efficient)
High (dry asphalt)	• AD Vehicle will drive too fast (not safe) • High frequency of accidents	Vehicle speed can be adapted to friction

Reference: [Matthijs Klomp, et al, 2019]

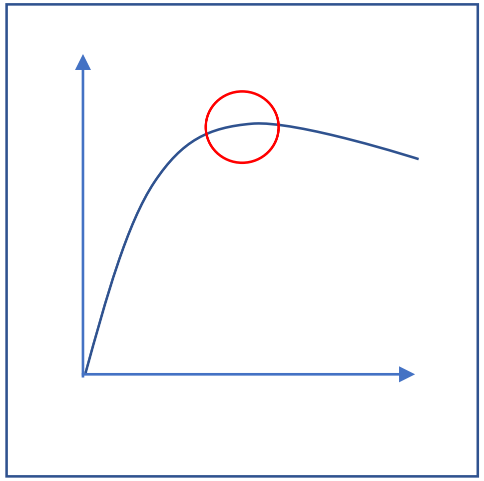
Methods for road friction estimation

Optical measurement device



- Contactless
- Requires a map from texture to friction

Model-based estimator

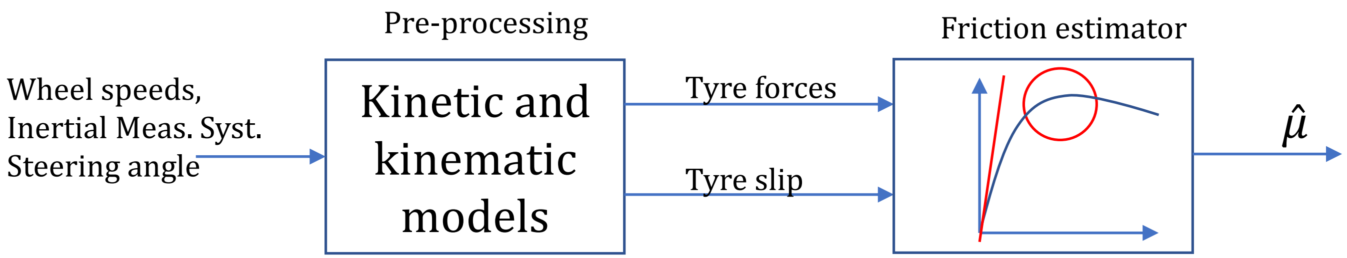


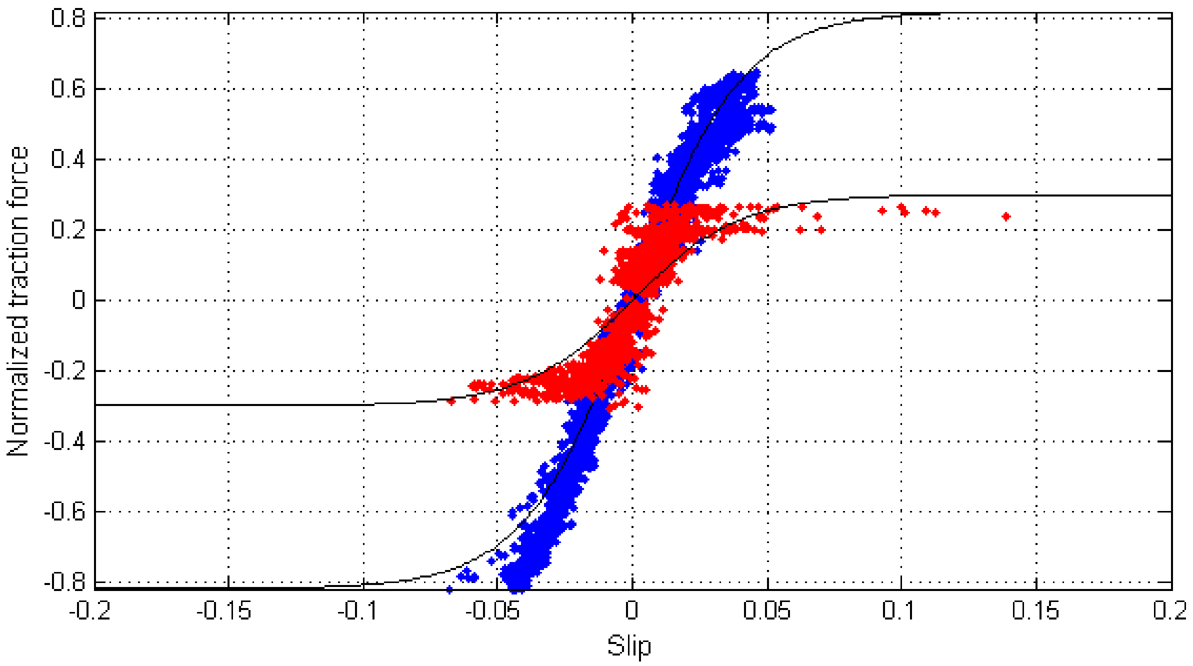
- Use the tyre as the sensor
- Requires knowledge about tyre physics

Machine learning estimator

- Use features without knowledge of physics
- Requires training

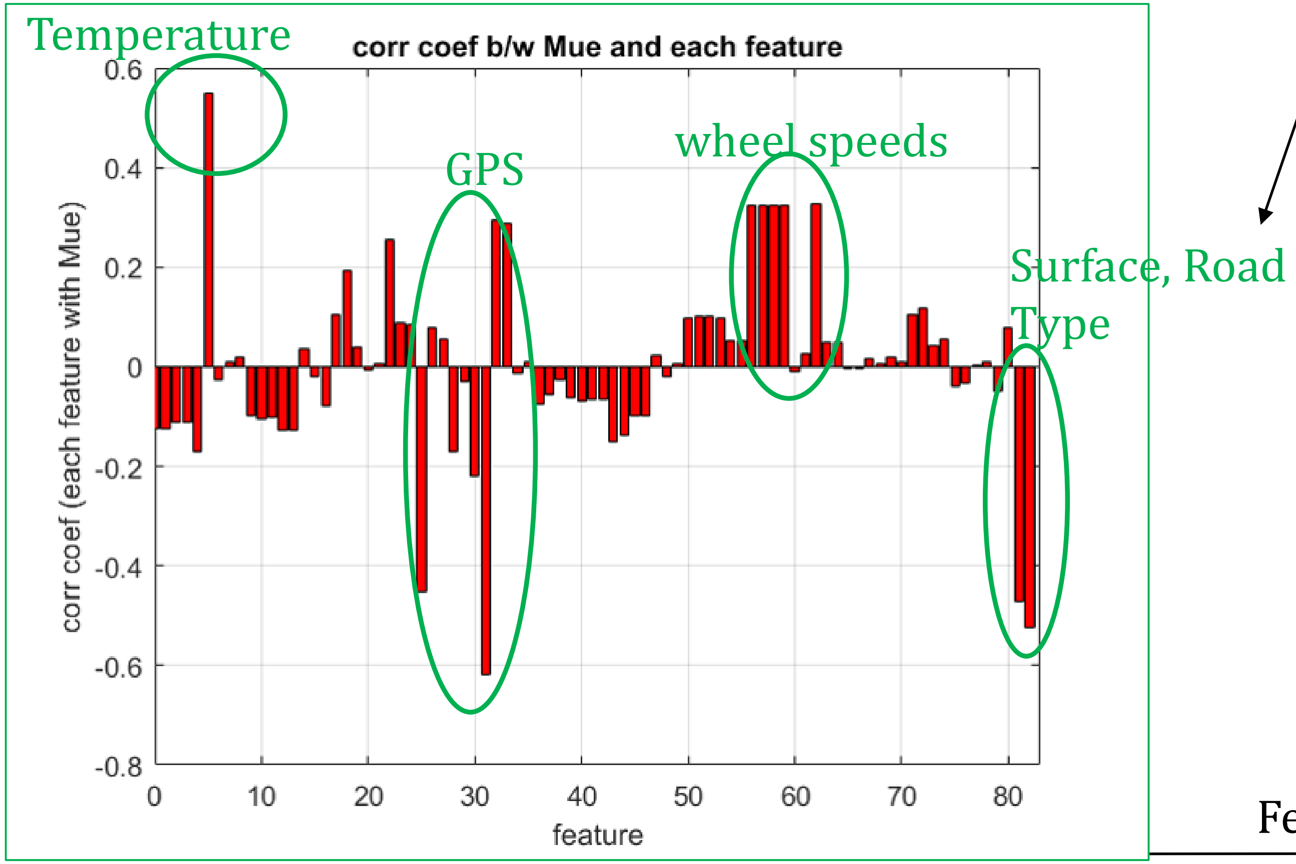
State-of-the art model-based estimator





Features and correlation to friction

Correlation to true friction



Features 1...86

Surface & road type are not available in the sensor suite -> important to use a new sensor e.g. a camera

Temperature, GPS, vehicle speed, surface and road type are important features for friction estimation

* Reference[Roychowdhury, et al, 2018]

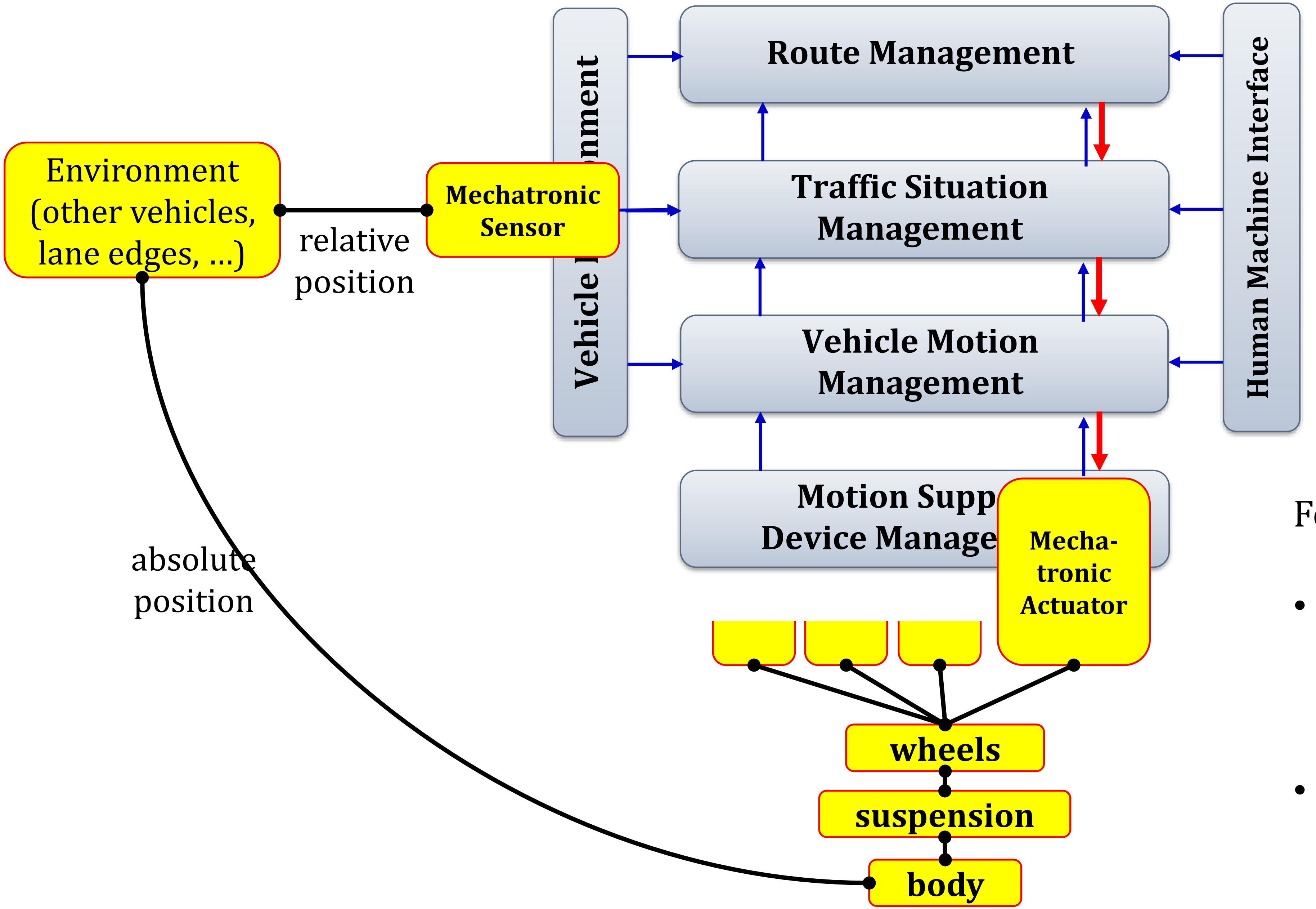
Challenges road friction estimation

- General:
  - Difficult to identify friction for normal driving (low friction utilization)
- Model-based:
  - Model uncertainties for different tyres - the physics is hard to model
  - The pre-processing is not accurate enough
- Machine learning:
  - Generalizability of machine learning algorithms to various situations
  - Generalizability would require large testing
  - Training of machine learning algorithms require ground truth – road friction is hard to measure

Reference [Jonasson, et al] 2018

Motion Devices, Virtual Verification, Wheel Model, Bengt Jacobson

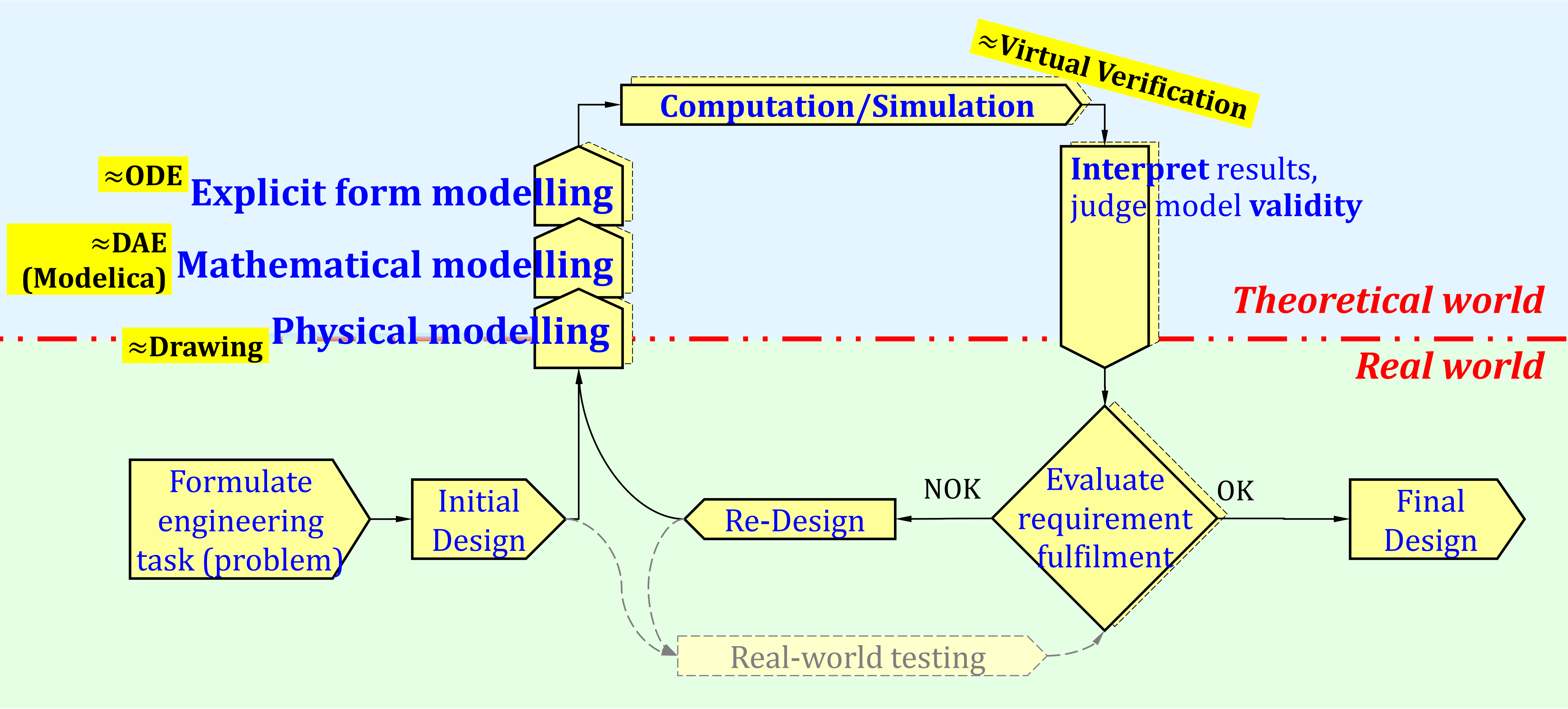
Models for Virtual Verification



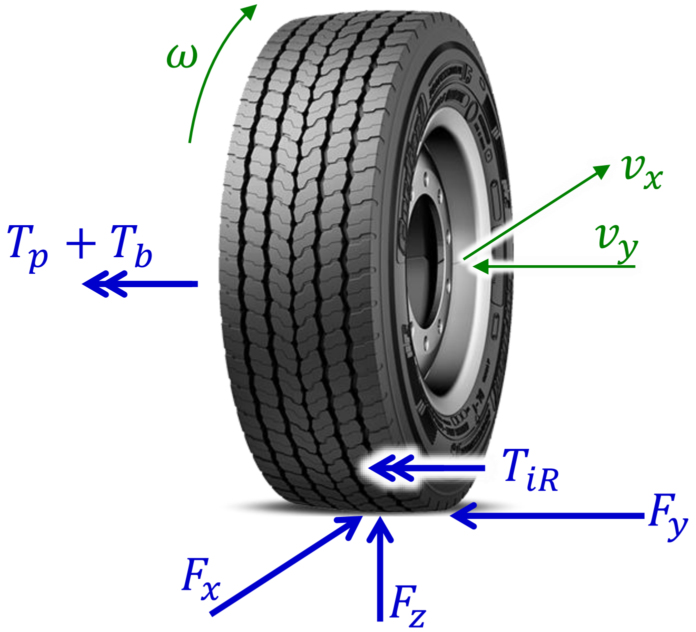
For Virtual Verification:

- Higher **accurate** and larger **validity** range than for control design.
- But **only simulate-able**, no need for linearized, inversion, etc.

...one view of model based engineering



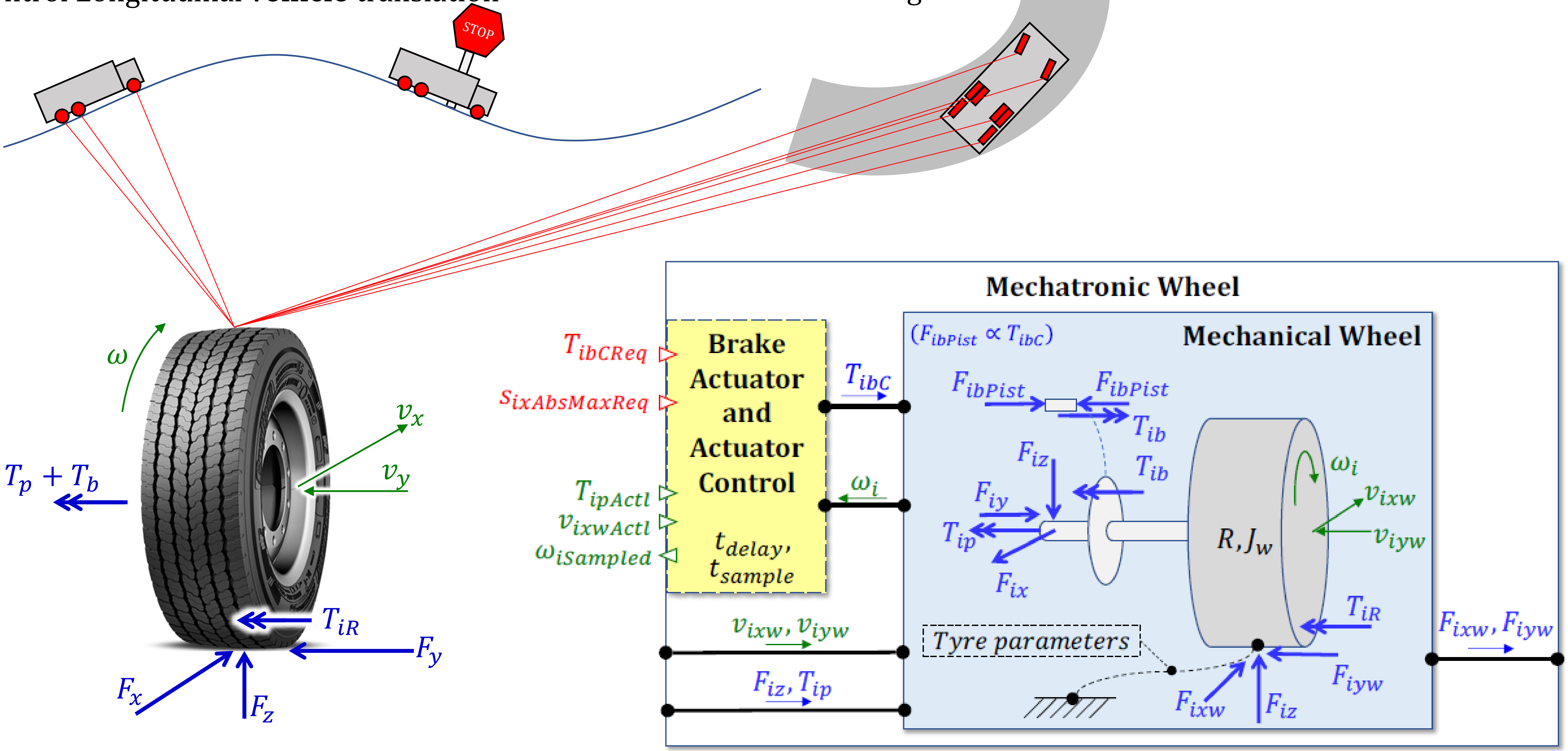
Wheel model as example



Wheel model use cases

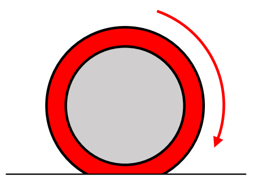
Control Longitudinal **vehicle** translation

Control Longitudinal **wheel** rotation



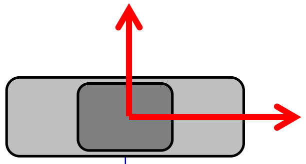
Wheel model, Mechanical challenges

Continuously Renewed Friction Surfaces



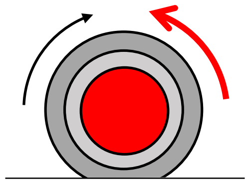
$$F_x = C_x \cdot s_x;$$
$$s_x = \frac{R \cdot \omega - v_x}{|R \cdot \omega|};$$

Relative Velocity Direction

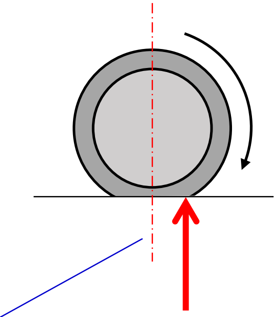


$$[F_x, F_y] = \min\left(C_{xy} \cdot s_{xy}, \mu \cdot F_z\right) \cdot \left[\sin\left(\theta_{Fxy}\right), -\cos\left(\theta_{Fxy}\right)\right];$$
$$s_{xy} = \frac{\sqrt{(R \cdot \omega - v_x)^2 + v_y^2}}{|R \cdot \omega|}; \theta_{Fxy} = arctan2\left(\underline{-v_y}, \underline{(R_w \cdot \omega - v_x)}\right);$$

Dry Friction in Brake

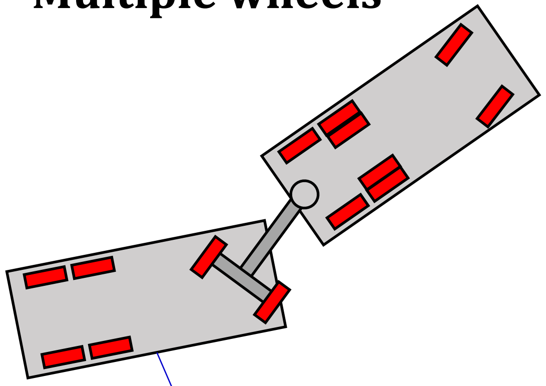


Rolling Resistance



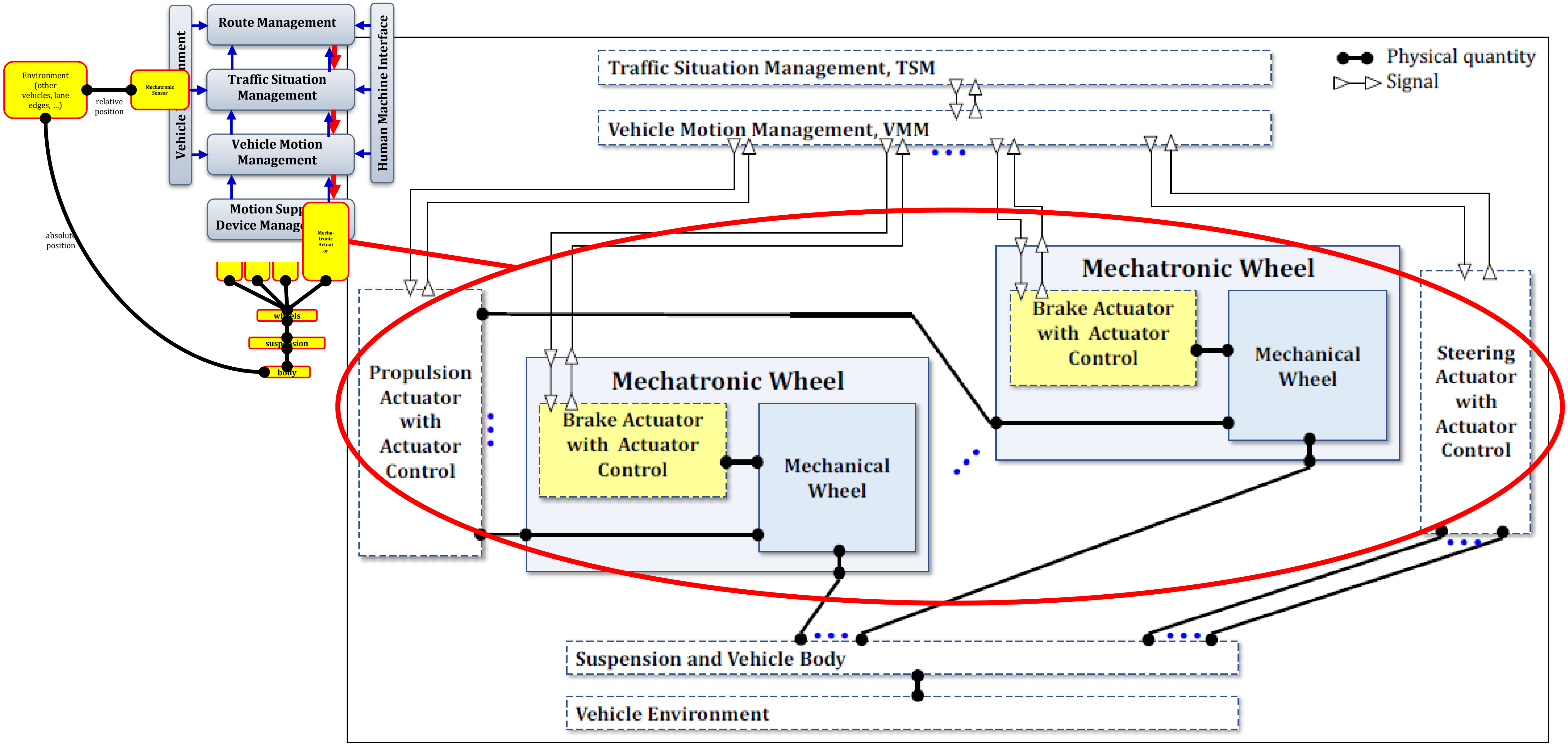
$$J \cdot \dot{\omega} = T - F_x \cdot R - T_R;$$
$$T_R = -\underline{\mathrm{sign}(\omega)} \cdot (T_{bC} + RRC \cdot R \cdot F_z);$$

Multiple wheels



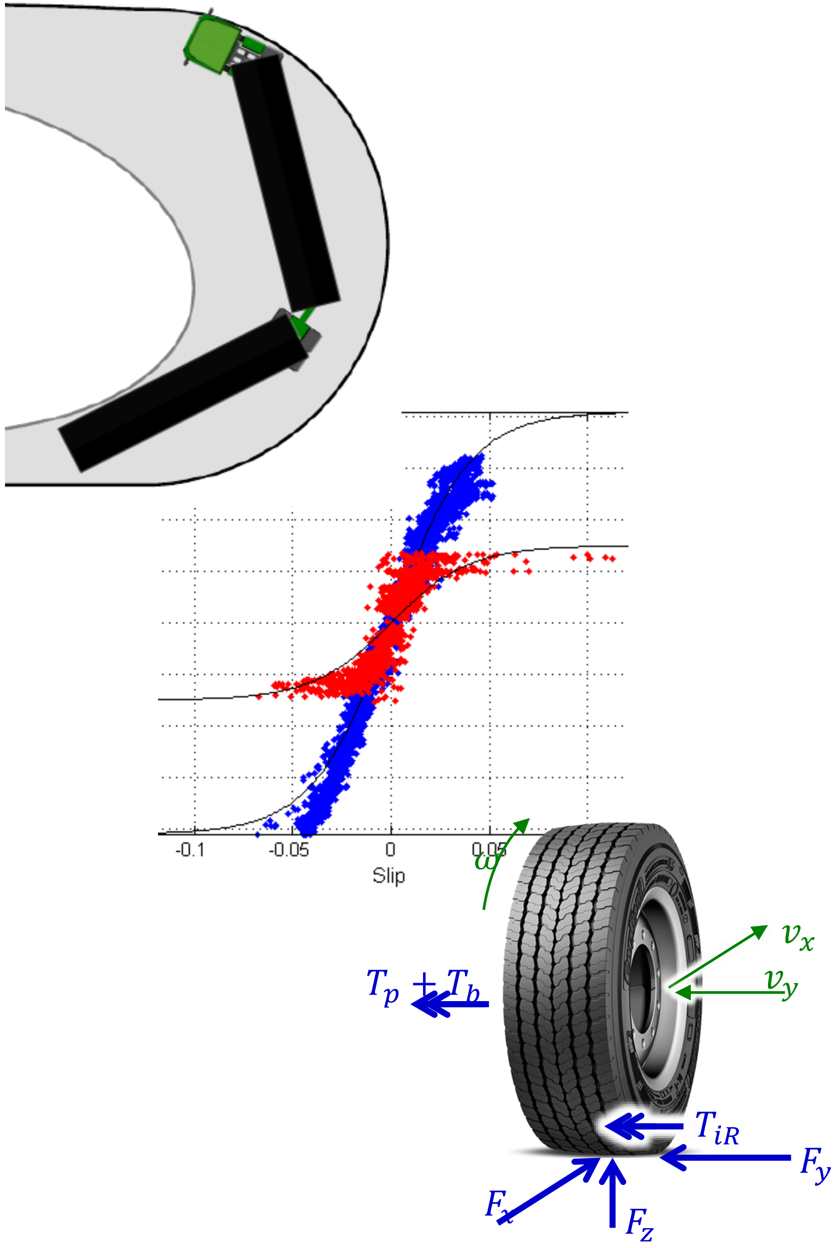
If vehicle standstill and two or more wheels locked:
Statically underdetermined

Wheel model in its model context



Conclusions

You have seen:



Automated driving needs modelling in many aspects:

- TSM and VMM needs Physical modelling for "**Control/algorithm design**".
- "**Virtual verification**" drives Physical modelling, incl. exchange of models between organisation.

References

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Thanks for your attention